Markov Chain Monte Carlo

Theory and Practical applications

Chapter 4: Geometric ergodicity and CLT

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1 Introduction

2 Coupling and total variation

3 Geometric ergodicity

4 Central Limit theorem

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4 Central Limit theorem

Geometric ergodicity means that there exists constants $C > 0$ and $\varrho \in (0, 1)$ such that for all $n \in \mathbb{N}$,

$$\|\mu P^n - \pi\|_{\mathrm{TV}} \leqslant C\varrho^n$$

where $\|\cdot\|_{\mathrm{TV}}$ is the total variation norm (to be defined later) between two measures.

1. μP^n is the law of X_n starting from $X_0 \sim \mu$
2. π is the law of X_n starting from $X_0 \sim \pi$
3. Geometric ergodicity for Markov chains should not be confused with the notion of ergodic dynamical systems

CLT means that

$$n^{-1/2} \sum_{k=0}^{n-1} \{h(X_k) - \pi(h)\} \overset{\mathcal{L}_{\mathbb{P}_\pi}}{\Rightarrow} \mathcal{N}(0, \sigma_\pi^2(h))$$

where h belongs to some class of functions and σ_π should be explicit.

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Definition

Let $(\mathsf{X}, \mathcal{X})$ be a measurable space and let ν, μ be two probability measures on $(\mathsf{X}, \mathcal{X})$. We define $\mathcal{C}(\mu, \nu)$, the coupling set associated to (μ, ν) as follows

$$\mathcal{C}(\mu, \nu) = \{\gamma \in \mathsf{M}_1(\mathsf{X}^2) \,:\, \gamma(\cdot \times \mathsf{X}) = \mu(\cdot), \gamma(\mathsf{X} \times \cdot) = \nu(\cdot)\}$$

Any $\gamma \in \mathcal{C}(\mu, \nu)$ is called a coupling of (μ, ν).

1. In words, γ is a coupling of (μ, ν) if the following property holds: if $(X, Y) \sim \gamma$, then we have the marginal conditions: $X \sim \mu$ and $Y \sim \nu$.
2. Example: The law of (X, X) where $X \sim \mu$ is a coupling of (μ, μ). Other example if $X \sim \mu$ and $Y \sim \mu$ and $X \perp Y$, then, the law of (X, Y) is a coupling of (μ, μ).

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Let $(\mathsf{X}, \mathcal{X})$ be a measurable space and let ν, μ be two probability measures $\mu, \nu \in \mathsf{M}_1(\mathsf{X})$. Then the total variation norm between μ and ν noted $\|\mu - \nu\|_{\mathrm{TV}}$, is defined by

$$\|\mu - \nu\|_{\mathrm{TV}} = 2 \sup \{|\mu(f) - \nu(f)| \,:\, f \in \mathsf{F}(\mathsf{X}), 0 \leqslant f \leqslant 1\} \tag{1}$$

$$= \int |\varphi_0 - \varphi_1|(x)\zeta(\mathrm{d}x) \tag{2}$$

$$= 2 \inf \{\mathbb{P}(X \neq Y) \,:\, (X, Y) \sim \gamma \text{ where } \gamma \in \mathcal{C}(\mu, \nu)\} \tag{3}$$

where $\mu(\mathrm{d}x) = \varphi_0(x)\zeta(\mathrm{d}x)$ and $\nu(\mathrm{d}x) = \varphi_1(x)\zeta(\mathrm{d}x)$.

Proof is given in the lecture notes

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Assumption A1

[**Minorizing condition**] for all $d > 0$, there exists $\epsilon_d > 0$ and a probability measure ν_d such that

$$\forall x \in C_d := \{V \leqslant d\}, \quad P(x, \cdot) \geqslant \epsilon_d \nu_d(\cdot) \tag{4}$$

Assumption A2

[**Drift condition**] there exists a constants $(\lambda, b) \in (0,1) \times \mathbb{R}^+$ such that for all $x \in \mathsf{X}$,

$$PV(x) \leqslant \lambda V(x) + b$$

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Theorem

(Forgetting of the initialization) *Assume (A1) and (A2) for some measurable function $V \geqslant 1$. Then, there exists a constant $\varrho \in (0,1)$ such that for all $x, x' \in \mathsf{X}$ and all $n \in \mathbb{N}$,*

$$\left\| P^n(x,\cdot) - P^n(x',\cdot) \right\|_{\mathrm{TV}} \leqslant \varrho^n \left[V(x) + V(x') \right] .$$

Proof is hard. It is given in the lecture notes.

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Corollary

(Geometric ergodicity) *Assume that (A1) and (A2) hold for some measurable function $V \geqslant 1$. Then, the Markov kernel P admits a unique invariant probability measure π. Moreover, $\pi(V) < \infty$ and there exists constants $(\varrho, \alpha) \in (0,1) \times \mathbb{R}^+$ such that for all $\mu \in \mathsf{M}_1(\mathsf{X})$ and all $n \in \mathbb{N}$,*

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Proof should be done on the blackboard

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- Recap on martingales
- The Poisson equation
- Central limit theorems

Let $(M_n)_{n\in\mathbb{N}}$ be a sequence of random variables on the same probability space $(\Omega, \mathcal{F}, \mathbb{P})$ and let $(\mathcal{F}_n)_{n\in\mathbb{N}}$ be a filtration (ie for all $n \in \mathbb{N}$, $\mathcal{F}_n \subset \mathcal{F}_{n+1} \subset \mathcal{F}$).

Definition

We say that $(M_n)_{n\in\mathbb{N}}$ is a $(\mathcal{F}_n)$-martingale if for all $n \in \mathbb{N}$, M_n is integrable and for all $n \geqslant 1$,

$$\mathbb{E}[M_n|\mathcal{F}_{n-1}] = M_{n-1}$$

The *increment process* of the martingale is by definition $(M_{n+1} - M_n)_{n\in\mathbb{N}}$.

Theorem

If a sequence $(M_n)_{n\in\mathbb{N}}$ is a $(\mathcal{F}_n)$-martingale with stationary and square integrable increments, then

$$n^{-1/2} M_n \stackrel{\mathcal{L}_{\mathbb{P}}}{\Rightarrow} \mathcal{N}\left(0, \mathbb{E}[(M_1 - M_0)^2]\right)$$

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Definition

For a given measurable function h such that $\pi|h| < \infty$, the Poisson equation is defined by

$$\hat{h} - P\hat{h} = h - \pi(h) \tag{5}$$

A solution to the Poisson equation is a function $\hat{h}$ for which (5) holds provided that $P|\hat{h}|(x) < \infty$ for all $x \in \mathsf{X}$.

Link between Poisson equations and Martingales

Define

$$S_n(h) = \sum_{k=0}^{n-1} \{h(X_k) - \pi(h)\}$$
$$= M_n(\hat{h}) + \hat{h}(X_0) - \hat{h}(X_n)$$

where

$$M_n(\hat{h}) = \sum_{k=1}^{n} \left\{\hat{h}(X_k) - P\hat{h}(X_{k-1})\right\} \quad (6)$$

Note that $\left\{M_n(\hat{h})\right\}_{n\in\mathbb{N}}$ is indeed a $(\mathcal{F}_k)$-martingale where $\mathcal{F}_k = \sigma(X_0, \ldots, X_k)$. Indeed we have

$$\mathbb{E}[M_n(\hat{h})|\mathcal{F}_{n-1}] - M_{n-1}(h) = \mathbb{E}[\hat{h}(X_n) - P\hat{h}(X_{n-1})|\mathcal{F}_{n-1}]$$
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Theorem

Assume that (A1) and (A2) hold for some measurable function $V \geqslant 1$. Then, for any function h such that $|h| \leqslant V$, the function

$$\hat{h} = \sum_{n=0}^{\infty} \{P^n h - \pi(h)\} \tag{7}$$

is well-defined. Moreover, $\hat{h}$ is a solution of the Poisson equation associated to h and there exists a constant γ such that for all $x \in \mathsf{X}$,

$$|\hat{h}(x)| \leqslant \gamma V(x)$$

Proof should be done on the blackboard

Theorem

(CLT with Poisson assumption) *Let P be a Markov kernel with a unique invariant probability measure π. Let $h \in \mathrm{L}^2(\pi)$. Assume that there exists a solution $\hat{h} \in \mathrm{L}^2(\pi)$ to the Poisson equation $\hat{h} - P\hat{h} = h$. Then*

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